



# Mapping development potential of dry-season small-scale irrigation in Sub-Saharan African countries under joint biophysical and economic constraints - An agent-based modeling approach with an application to Ethiopia

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## ABSTRACT

Sub-Saharan Africa has long been beset with food insecurity. Investment in small-scale irrigation may provide a solution to address the challenge by extending crop production into the dry season. We present an agent-based modeling system to assess the potential of dry-season small-irrigation development in Sub-Saharan Africa with an application to Ethiopia. We identify significant potential for investing in dry-season small-scale irrigation in Ethiopia and map geographic domains with highest investment opportunities.

## 1. Introduction

Sub-Saharan Africa is home to about one billion people (UN, 2017) and agriculture remains the dominant livelihood in the region. Although remarkable progress in agricultural development has been achieved in Sub-Saharan Africa over the past few decades, population growth has been too fast and both agricultural and overall economic growth too slow for food security challenges to abate (FAO, 2016; World Bank, 2018). A key reason for the sub-optimal performance of the agricultural sector has been low level of input and technology use, including a low level of irrigation development. Globally, irrigated agriculture accounts for approximately 20% of cropland but contributes to 40% of food production (WWAP, 2018). In Sub-Saharan Africa, using official data from FAO AQUASTAT it is estimated that only 4% of cropland in Sub-Saharan Africa is equipped with irrigation (Svendsen et al., 2009). Although there is perception that irrigated area in Sub-Saharan Africa may be under-reported, such a low percentage of irrigated land area undoubtedly suggests that irrigation development in Sub-Saharan Africa far lags behind other regions of the world. The dependency on rainfall

leaves agricultural production in Sub-Saharan Africa vulnerable to variability in precipitation. Ensuring efficient and effective water management through irrigation is essential for raising agricultural productivity and helping achieve the Malabo Declaration commitment to end hunger in Africa. Moreover, apart from increased food production under variable climate, expanded irrigated agriculture also implies the production of more diverse, nutrient-dense crops, such as vegetables, the generation of higher incomes and serves as an entry point for women's empowerment (Domènech, 2015).

While the low level of irrigation development suggests a vast potential for expansion, policymakers and investors require more detailed knowledge on the location of irrigation potential, to ensure that development is sustainable under climate and hydrological constraints and responsive to market and food demand needs.

This paper presents an innovative approach to map national development potential of small-scale, dry-season irrigation in Sub-Saharan African countries. Small-scale irrigation is also often called distributed irrigation, small private irrigation, smallholder irrigation or farmer-led irrigation (Kay, 2001; Burney et al., 2013; de Fraiture and Giordano,

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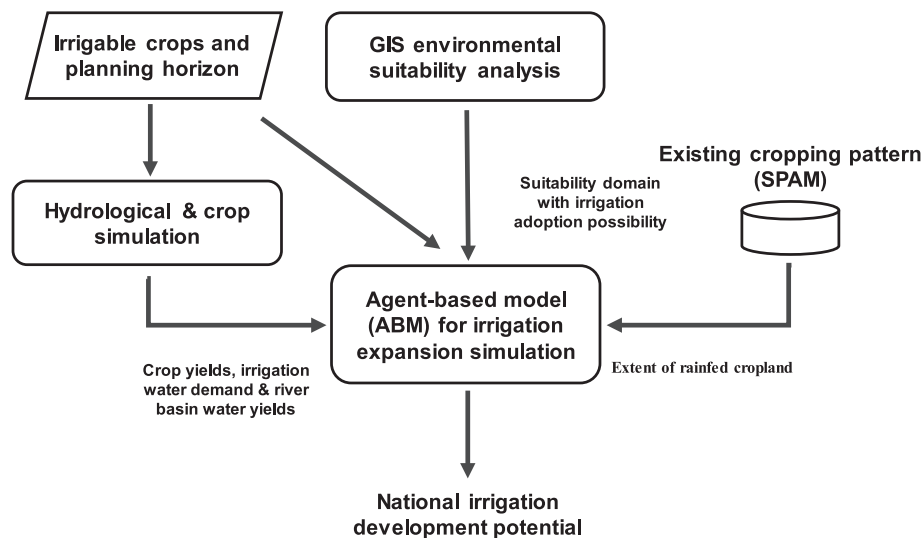


Fig. 1. Integrated modeling framework for mapping small-scale irrigation development potential.

2014; Lefore et al., 2019). There might be no single agreed upon definition or term for this type of irrigation, but generally speaking, in small-scale irrigation both the technology to irrigation and access to the water-source is self-supplied by individual farmers or small groups of farmers, and each farmer decides which technology to procure, what water source to tap and what to plant and sell. It is thus distinct from large-scale irrigation development, which typically involves building large dams for water storage, is publicly financed and an outcome of central planning. There is keen interest in recent years to promote the development of small-scale irrigation because it not only addresses the long-term neglect and underinvestment by public agencies but has also been shown to be more cost-effective than large-scale irrigation (You et al., 2011). This advantage of small-scale irrigation is due, in part, to the elevated autonomy of individual irrigators, which motivates the development of the agent-based modeling tool in this study.

In addition to distinguishing between small-scale and large-sale irrigation, we also differentiate between irrigation activities in the dry and rainy seasons and limit our attention to dry-season irrigation for the purpose of this study. Sub-Saharan Africa stretches across the equator. Most parts of the region have a tropical climate with alternating dry and rainy seasons. Difference in agricultural water management between the two seasons has been observed. Compared to rainy-season irrigation, which is generally applied on staple crops to supplement gaps in precipitation, irrigation in the dry season is generally profit-oriented and used for the production of cash crops (Asayehegn et al., 2011; Takeshima and Edeh, 2013; Namara et al., 2014) in environments where production would otherwise not be feasible.

Several prior studies assessed the irrigation development potential in Africa at national and continental scales. Some of these studies used GIS (Geographic Information System) tool and MCE (Multi-Criteria Evaluation) technique, in which environmental suitability for irrigated development is evaluated using selected environmental criteria (Mati et al., 2006; Diouf et al., 2017; Schmitter et al., 2018). Irrigation development potential in Sub-Saharan Africa was also defined using water budget approach. For example, Altchenko and Villholth (2015) evaluated irrigation potential from renewable groundwater in Africa based on current cropping patterns and annual groundwater balance information derived from hydrological and crop water demand modeling. Finally, more integrated hydro-economic methodology has been developed for national and regional irrigation planning in Sub-Saharan Africa by Xie et al. (2014, 2017). The method combines use of GIS environmental suitability analysis, hydrological and crop simulation and economic cost-benefit analysis tools. At the core of the

integrated modeling framework is a sectoral model which optimizes placement of irrigation investment within geo-domains pre-determined by GIS environment suitability analysis by maximizing total profits of the agricultural sector under water availability and food demand constraints. In this process, irrigation development is recognized as a driver of cropping pattern change; both irrigated area and crop mix are no longer input variables subject to scenario analysis but a result from the analysis.

To further advance small-scale irrigation development planning and building on Xie et al. (2014, 2017), in this paper we present an innovative agent-based model to overcome limitations in the earlier, optimization-based approach. Agent-based modeling provides a bottom-up approach to model complex coupled natural-human systems by decomposing the real-world system into a large number of autonomous entities, or agents, and simulating the behaviors of agents at individual level (Berger, 2001; Bonabeau, 2002; Kennedy, 2012; Filatova et al., 2013). As such, the decision to adopt small-scale irrigation for dry-season agricultural production is simulated at the farm level and the irrigation development potential is inferred from the spatial pattern of small-scale irrigation adoption emerging from the micro-level simulation of irrigation adoption behaviors. We consider agent-based modeling as a more appropriate technique to simulate small-scale irrigation since small-scale irrigation is essentially a distributed system and there is no central agency in charge of the adoption decisions of small-scale irrigation technologies.

The development of the agent-based planning model is illustrated for the case study of Ethiopia, a country located in the Horn of Africa covering 1.1 million km<sup>2</sup> of land. The Government of Ethiopia has developed a small-scale irrigation strategy and is keenly interested in accelerating agricultural intensification through expanding irrigated production across the country as part of its growth and transformation strategy (NPC, 2015; FAO and IFC, 2015).

## 2. Data and method

The assessment framework, which builds on Xie et al. (2014, 2017) is presented schematically in Fig. 1. While the goal of the paper is to report the newly developed agent-based planning model, other key steps in this framework are first described in Sections 2.1 and 2.2.

### 2.1. Irrigable crops and planning horizon

As indicated in Fig. 1, to launch the assessment it is necessary to

**Table 1**  
Irrigable crops and their yields considered in the study

Irrigable crops		Yields (ton/ha)
Vegetables	Tomatoes	19.8
	Onions	9.3
	Cabbages	15.4
	Peppers	2.3
	Other	4.3
Pulses	Chickpeas	3.3
	Other	2.7
Fodder		9.6

1. Fodder yield refers to dry matter yield.

specify a collection of irrigable crops farmers might choose to cultivate once they opt for irrigation, as well as the planning horizon of the assessment. A list of irrigable crops considered in Ethiopia case study is listed in Table 1. Based on household survey data (for example, Pas-sarelli et al., 2018) and a literature review, we identify vegetables as key dry-season irrigated crops in the country (Alemayehu et al., 2010; Emana et al., 2015; Nigussie et al., 2015), as well as irrigated pulses, such as chickpea (Bizimana et al., 2015). Irrigated fodder is not yet widely observed in the country but has been identified as a promising option to expand feed resources and support livestock production in Ethiopia and was therefore added to the crop selection (Wondatir et al., 2015).

We define irrigation development potential as the maximum spatial extent of small-scale irrigation under the joint constraints of water availability and market opportunities for the selected irrigated crops in the dry season. As such, irrigation potential is a dynamic concept which

varies with socioeconomic conditions and climate change. For this study we consider 2010 as base year and a planning horizon of 2030. Due to the relatively short term of the planning horizon, climate change is not considered. Furthermore, because of sustainability considerations and uncertainty in modeling land use (e.g., between agriculture and other land use types), irrigation adoption within the planning horizon was assumed to only occur within the extent of current rainfed cropland.

2.2. Environmental suitability analysis, SWAT simulation and SPAM

GIS-based Multi-Criteria Evaluation (MCE) analysis provides valuable information of the environmental suitability of irrigation development. The modeling framework in Fig. 1 incorporates a GIS-based MCE analysis on environmental suitability analysis for smallholder irrigation adoption. A GIS data layer (Fig. 2) derived from a MCE environmental suitability analysis for Ethiopia by Worqlul et al. (2017) was directly used in this study. The factors considered by Worqlul et al. (2017) include physical land features (land use, soil and slope etc.) and market access (proximity to roads). A table showing the list of factors considered in the study and the data sources for each variable can be found in Supplement S1. These factors were weighted using a pair-wise comparison matrix, reclassified, and overlaid to compute pixel-wise scores for environmental suitability of small-scale irrigation adoption on a 1 km by 1 km grid. The calculated environmental suitability score ranges from 30 to 97 with a full score of 100. Larger score values indicate better environmental suitability for small-scale irrigation adoption.

The assessment framework presented in Fig. 1 also involves hydro-logical and crop simulation modeling to generate spatial estimates of available water resources, attainable irrigated crop yields, and crop

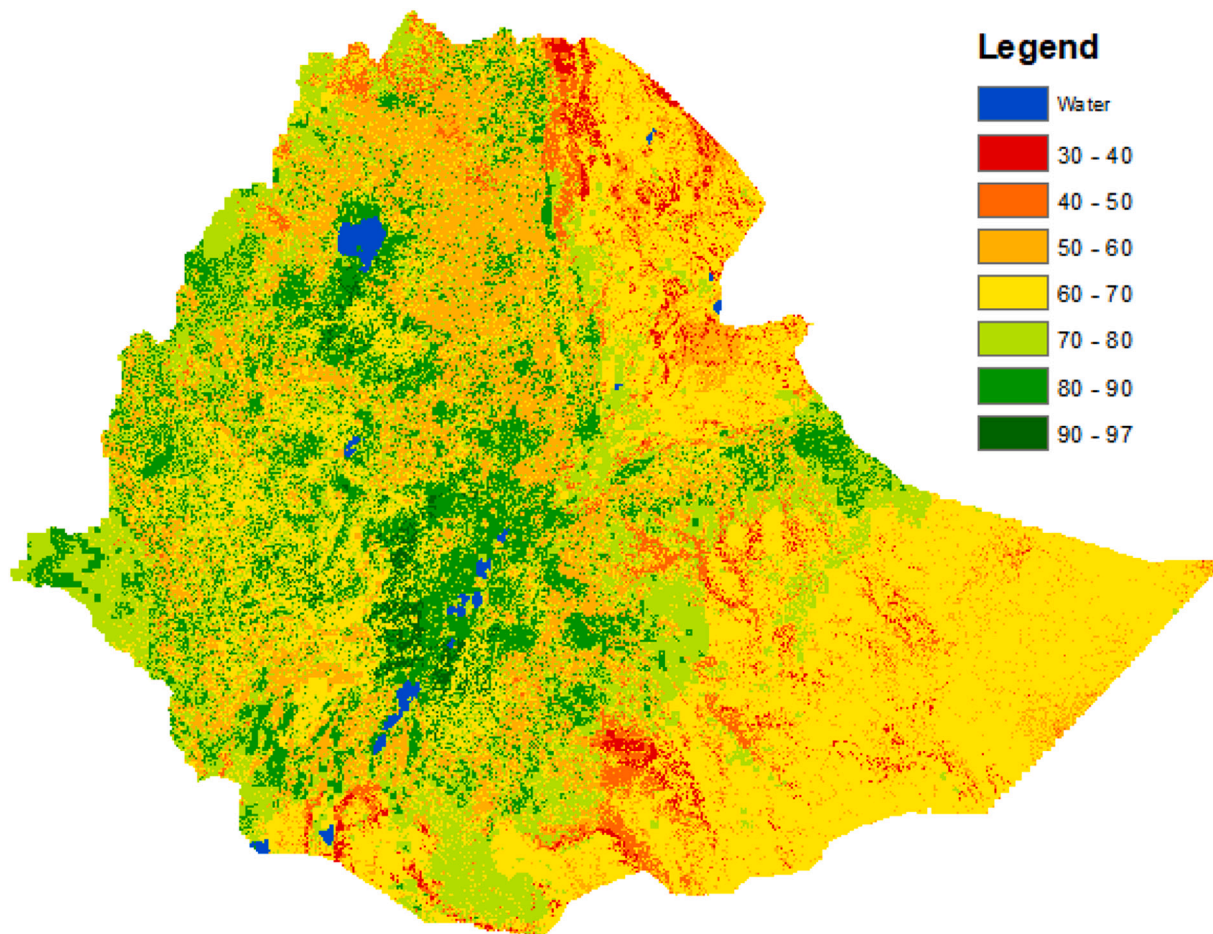


Fig. 2. Environmental suitability for small-scale irrigation development in Ethiopia (Worqlul et al., 2017).

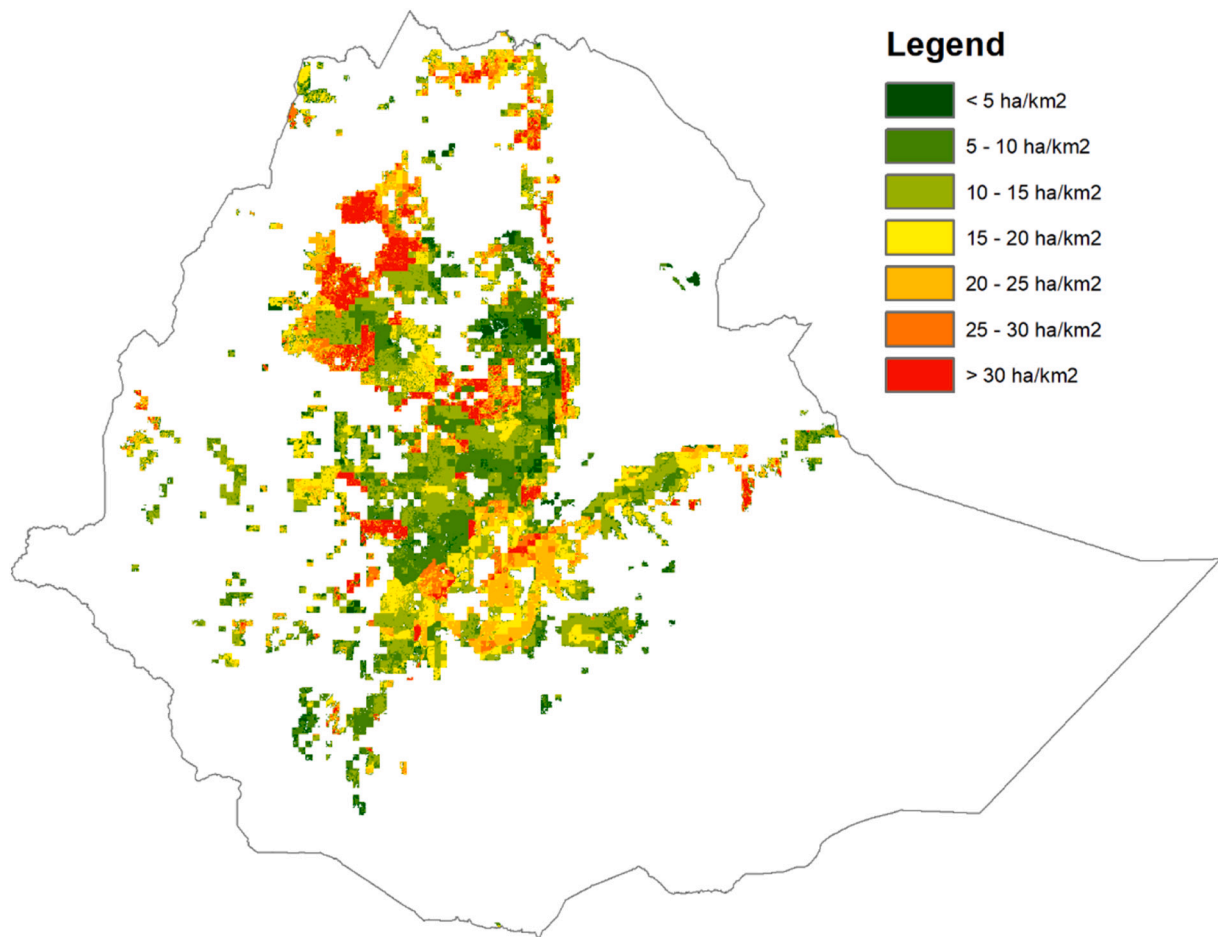


Fig. 3. Spatial distribution of rainfed cultivation area (farm size) of non-perennial crops in Ethiopia on 1 km × 1 km grid.

irrigation water demands. In this study on Ethiopia, we set up a SWAT (Soil and Water Assessment Tool) model covering the country using a grid-based approach to simulate these values on a 10 km by 10 km grid (with a simulation period of 1983–2013; see more details on this SWAT-Ethiopia model set up and its performance in Supplement S2). SWAT (Arnold et al., 1998) is a comprehensive watershed model. It is equipped with hydrological and crop simulation modules and functions for simulating various water and land management practices, including irrigation, and has a proven track record of successful application globally (Gassman et al., 2007).

The third modeling tool used in the modeling framework is the Spatial Production Allocation Model (SPAM) (You et al., 2014). SPAM is designed to downscale national and sub-national agricultural statistics for crop production to a fine grid. Global SPAM data ([www.mapSPAM.info](http://www.mapSPAM.info)) has a resolution of 5 arc-minute (approximately 10 km × 10 km on equator). For this study, a finer-resolution scale SPAM database was developed for Ethiopia for approximately 2010 with a resolution of 1 km by 1 km. Pixels in the SPAM 1 km grid coincide with pixels in environmental suitability 1 km grid. Estimates for cultivation area in each pixel by crop and by production system (rainfed or irrigated) are provided.

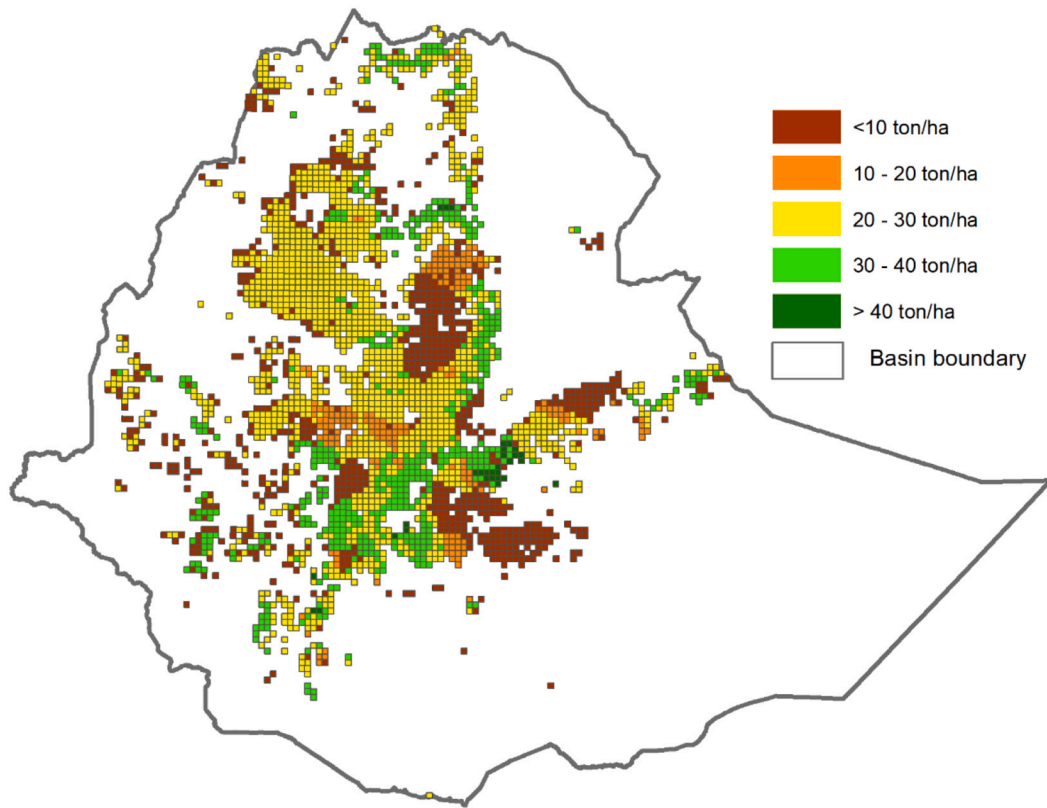
How the environmental suitability layer, SPAM data and output from SWAT hydrological and crop simulation are used to inform the agent-based simulation for expansion of small-scale irrigation is explained in next section where the agent-based planning model is presented.

### 2.3. Agent-based model (ABM) for modeling small-scale dry-season irrigation expansion

#### 2.3.1. Agent definition and attributes

For this study, we develop an agent-based irrigation planning model at the national scale. A class of agents, referred to as farms, are defined on the 1 km by 1 km environmental suitability/SPAM grid. Each cell on the grid with rainfed cropland is viewed as a farm. Agent attributes include farm size, environmental suitability for irrigation and farm productivity. Farm size is the SPAM estimate for rainfed area in the cell with perennial crop areas being excluded (Fig. 3). The environmental suitability for irrigation for each farm is characterized by suitability scores as described in Section 2.2. Farm productivity is characterized by the yields of irrigable crops (ton/ha) and associated irrigation water use intensities during the growing season (expressed in m<sup>3</sup> H<sub>2</sub>O per hectare per season/year). Estimates for both variables for each irrigable crop were generated using SWAT. What is worth noting is that SWAT considers effects of water stress, temperature stress and nutrient stress in crop simulation for yield estimation. There are, however, other technical and management factors (e.g. pesticides) which could affect crop yields. We therefore adjusted the potential yields obtained from the SWAT simulation by applying damping factors to account for the impact of these non-modeled factors on yield while preserving the spatial variability of yields projected by the model (Xie et al., 2017). The second column of Table 1 shows the average, national yields of irrigable crops considered in this case study. Fig. 4 (a) and Fig. 4 (b) illustrate estimated yields and associated irrigation water use intensities for tomatoes. Since the SWAT model runs on a 10 km by 10 km grid, we let a farm assume values of attainable yields and irrigation water use intensities estimated

(a) Attainable yields-Example of tomatoes



(b) Irrigation water demand: Example of tomatoes

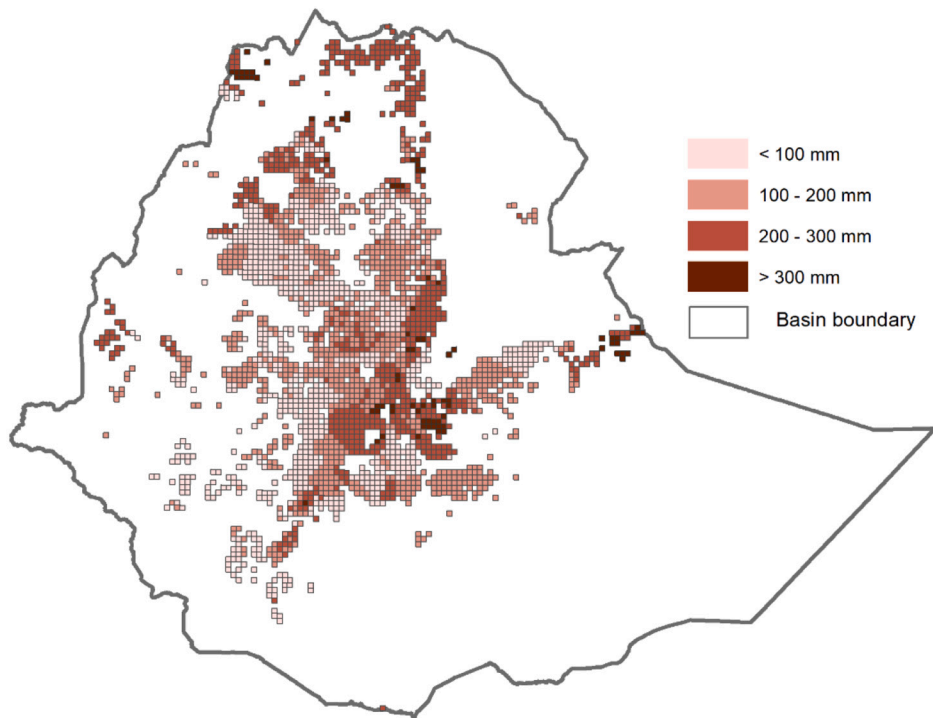


Fig. 4. Crop and hydrological simulation results from the Soil and Water Assessment Tool (SWAT) model on 10 km × 10 km grid.

## (c) Annual water yield

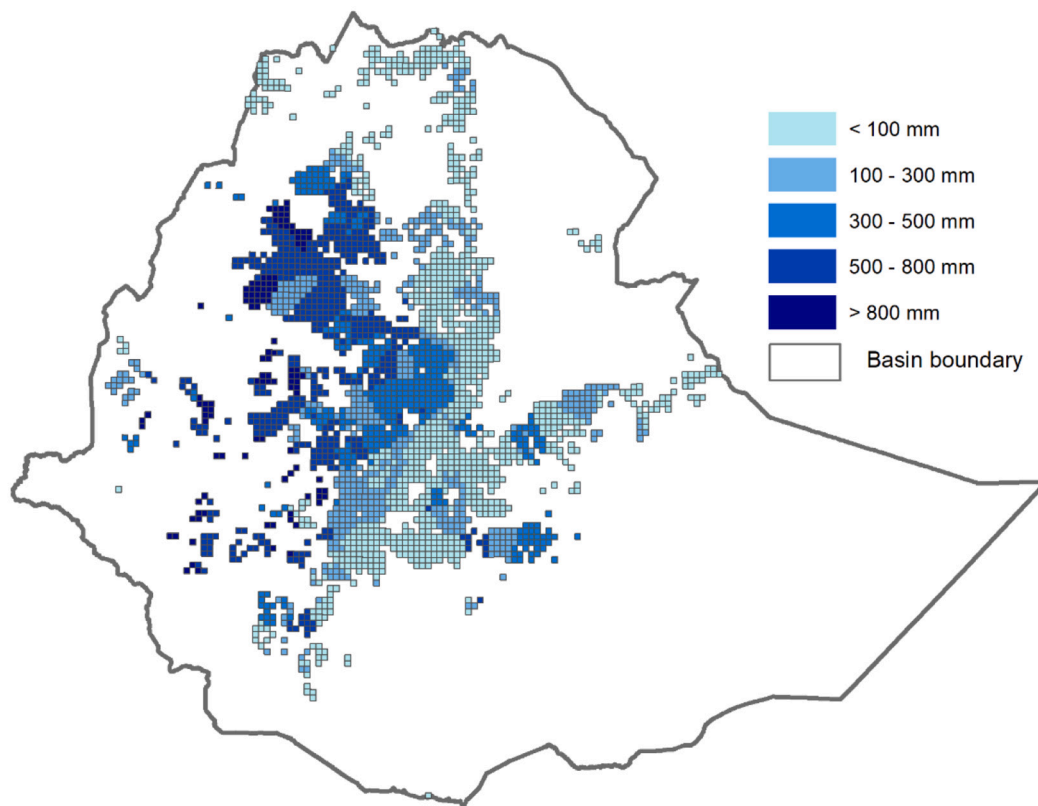


Fig. 4. (continued).

in 10 km cell where the farm is located. As there is currently no large irrigated fodder crop market in Ethiopia, we partitioned irrigated fodder into fodder used for meat and fodder used for milk production and used feed conversion ratios reported in Schmitter (2016) to derive the yields of meat and milk products from the yield of irrigated fodder. Profitability of producing irrigated fodder is defined by profits from the production chain.

### 2.3.2. Process overview

The agent-based model simulates irrigation expansion at multiple time steps. A time step in the simulation represents a growing season or year. At the beginning of each growing season, the adoption decision of each farm is evaluated under the assumption of bounded rationality. The consequences of irrigation are assessed at the end of each growing season. The model tracks farms' asset accrued from the irrigated production. Farms will exit irrigated production if asset values drop below zero. Prices of irrigated crops are modeled as endogenous variables. Increased supply of irrigated vegetables beyond demand will lower prices and this will, in turn, reduce the profitability of irrigated production and constrain the expansion of irrigation. Irrigation expansion is also constrained by water availability. Cells on the 10 km grid are used as spatial units of water accounting and in order to facilitate the discussion are referred to as basins.

The following describes the sub-models used to simulate the irrigation adoption decision as well as post-evaluation processes.

### 2.3.3. Sub-model for adoption decision

The decision processes reflected in the adoption sub-model is shown in Fig. 5. Firstly, the economic profitability of irrigated production is evaluated using expected producer prices of irrigable crops and on-farm costs of irrigated production. In the evaluation, the economic profit of

cultivating each irrigable crop is calculated as

$$NP_{c,t} = PP_{c,t}^e \cdot y_c - C_{irr} - C_{c,other} \quad (1)$$

where  $NP_{c,t}$  (\$/yr-ha) is economic profit from irrigated production of crop product  $c$  in year  $t$ ,  $PP_{c,t}^e$  is the farmer's expected producer price for the crop product (\$/ton),  $y_c$  is the irrigated crop yield derived from the SWAT simulation (ton/ha-yr),  $C_{irr}$  is irrigation cost (\$/ha-yr), and  $C_{c,other}$  refers to the non-irrigation component of the production costs (\$/ha-yr).

Price expectation is calculated as (Burton and Love, 1996):

$$PP_{c,t}^e = PP_{c,t-1} \quad (2)$$

where  $PP_{c,t-1}$  is the "actual" producer price in the preceding year (\$/ton). Producer prices at regional state level during 2012–2013 obtained from the Central Statistical Agency (CSA) of Ethiopia were used to initialize the simulation (CSA, 2013).

In Eq. (1), the production cost is broken down into two components. The non-irrigation-related component is estimated using a profit margin approach (Xie et al., 2017).

$$C_{c,other} = PP_{c,0} \cdot y_c \cdot (1 - pm_c) \quad (3)$$

where  $PP_{c,0}$  is the producer price in the base year (\$/ton) approximated using available sampled producer prices by region between July 2012–June 2013 (CSA, 2013),  $pm_c$  is the profit margin – a parameter defined to reflect the ratio of non-irrigation-related production costs (e.g., fertilizers, seeds, pesticides) to the total revenue in base year. Survey data on agricultural production costs, including irrigation cost, are extremely scarce. Knowledge which helps to determine values of cost parameters used in large-scale strategic irrigation planning analysis in

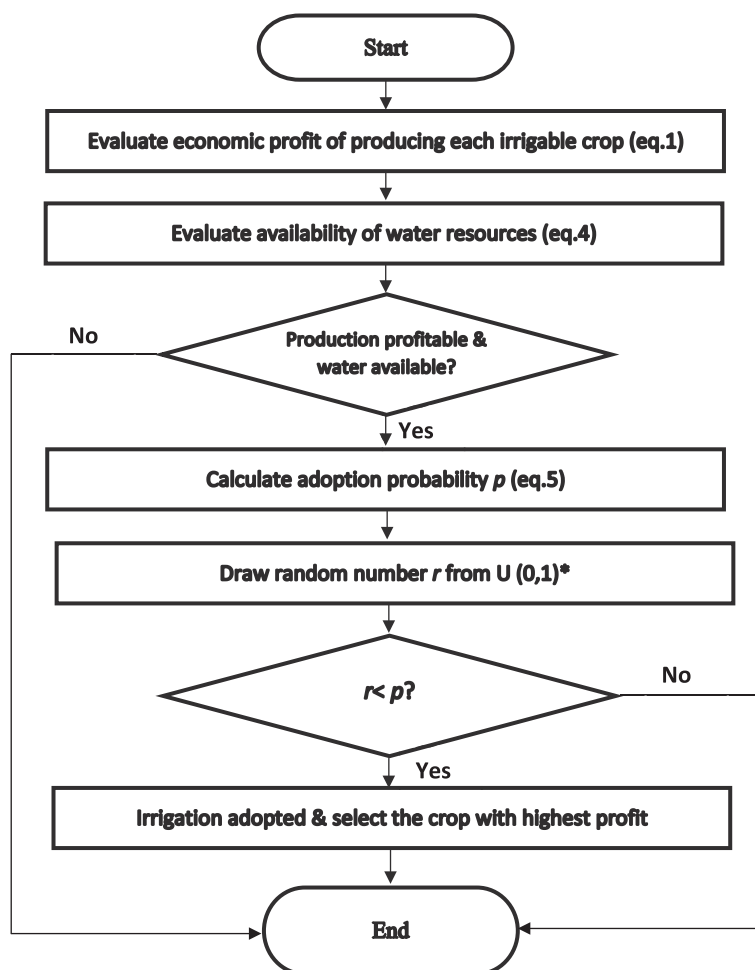


Fig. 5. Farm's decision process for irrigation adoption. \*U(0,1) denotes uniform distribution between 0 and 1.

Sub-Saharan African countries is mainly present in the form of expert opinion. Value of profit margin parameter was assumed to be 0.8 for all crops/products in the case study. Irrigation cost is a more prominent parameter in the context of this study. In addition to uncertainty arising from data scarcity, costs of irrigations could vary with configuration of irrigation systems. In this Ethiopia case study, the irrigation cost was first set to \$200/ha-yr – this cost level was chosen to reflect the costs associated with the purchase and operation of water lifting devices such as motor pumps - and is included in sensitivity analysis described in Section 2.4.

The expected economic return from irrigated farming is defined using the calculated profits from the most lucrative crop option. Irrigation adoption is only possible when the expected economic return is positive, and once irrigation is adopted, it is assumed that farm will cultivate the crop that is most profitable.

In addition to economic profitability, the sub-model also evaluates the water budget of the 10 km basin hosting the farm. The quantity of water resources available for irrigation at the beginning of each growing season is calculated as

$$WAI = WY \cdot \alpha - \sum_i w_i \cdot A_i \quad (4)$$

where  $WAI$  is the quantity of water resources available for irrigation ( $\text{m}^3 \text{H}_2\text{O}/\text{yr}$ ) in the basin,  $WY$  is the annual water yield of the host river basin in which the farm is located consisting of direct runoff and groundwater baseflow/recharge ( $\text{m}^3 \text{H}_2\text{O}/\text{yr}$ ),  $\alpha$  is an availability factor indicating the fraction of annual water yield which can be used for irrigation (0–1);  $A_i$  is the area of farms which have already adopted irrigation in the river

basin (ha), and  $w_i$  is the irrigation water use intensity ( $\text{m}^3 \text{H}_2\text{O}/\text{ha}\cdot\text{yr}$ ) of those farms. Irrigation adoption will only occur when the water resources allocated for irrigation in the host river basin have not yet been depleted or  $WAI > 0$ .

The simulated annual water yield by SWAT is shown in Fig. 4(c), which is adjusted by the availability factor  $\alpha$  to estimate the availability of water resources for irrigation. The value of availability factor reflects the storage capacity, which is either man-made or naturally formed, connected to the small-scale irrigation system as well as volume of water reserved to meet other demands. In particular, the risk of water scarcity in dry season is largely caused by the uneven temporal distribution of water resources between seasons. Storage capacity is therefore a key factor that determines performance of the small-scale irrigation system. In real world, small-scale irrigation may take various forms: it may be fed by surface water or groundwater, and the effort of expanding small-scale irrigation may involve development of storage capacities such as small reservoirs and community ponds, which are often viewed as a part of the irrigation system. There is a lack of data and knowledge to determine the configurations of small-scale irrigations systems at each location in a national-scale analysis. In this Ethiopia study, we thus did not explicitly differentiate different types of small-scale irrigation systems. The irrigation is firstly assumed to be dominantly surface water based, and the availability factor is uniformly set to 0.06, or 6% of annual water yield, which is approximately equal to 70% of the runoff in the dry season, is assumed to be available for the small-scale irrigation. These assumptions and using 10 km pixel as a spatial unit of water accounting are based on the notion that small-scale irrigation systems possesses only limited storage capacity and mainly harness local water

resources. As shown in Section 2.4, to address the uncertainty in the water availability, a sensitivity analysis on the availability parameter  $\alpha$  is conducted.

Finally, for those farms which meet the economic profitable and non-depletion conditions, an adoption probability is calculated based on the farm's environmental suitability score. We assume that the farm adopts irrigation based on this probability.

The adoption probability is calculated as

$$p = \begin{cases} \frac{P_{max}}{100 - S_{threshold}} \cdot (S - S_{threshold}) & S > S_{threshold} \\ 0 & \text{Otherwise} \end{cases} \quad (5)$$

where  $p$  is the adoption probability,  $S$  is the farm's environmental suitability score for irrigation adoption,  $S_{threshold}$  is a threshold of the environmental suitability score for irrigation adoption to occur,  $p_{max}$  is the maximum adoption probability corresponding to the environmental suitability score value 100. This probabilistic rule is proposed to account for the influence of environmental factors on irrigation adoption that cannot be fully reflected in the on-farm economic profitability and water budget evaluations. Additional discussion on this rule is provided in Section 2.4.

### 2.3.4. Sub-model for post-adoption evaluation

At the end of growing season in each year, the economic profitability of irrigated production is re-evaluated. In this re-evaluation, the expected price in Eq. (1) is substituted by the "actual" price of irrigated crops at the end of the season estimated as a result of changes in irrigated production.

Various approaches are available to forecast prices of agricultural commodities (Allen, 1994). The sub-model used to simulate price changes post-adoption in this study is adapted from the Dynamic Research EvaluAtion for Management (DREAM) model, a partial equilibrium single-product model designed to evaluate the economic impact of agricultural research and development (Alston et al., 1995; Wood et al., 2000). We assume 11 domestic markets, corresponding to the 11 administrative regional states of Ethiopia, reflecting regionally differentiated price information. Producer prices in previous sections thus actually refer to producer prices in region where the farm is located. Trade data from the detailed trade matrix in the FAOSTAT database show that there are substantial exports of vegetables and pulses. An additional market representing the "Rest Of World" (ROW) is thus defined for these crops, which include major export destination countries identified based on the FAOSTAT trade matrix database. Due to lack of seasonal data, market is cleared on an annual basis.

Specifically, for each irrigated crop in a particular regional market, a linear demand function is specified:

$$C_{c,r,t} = \gamma_{c,r} + \delta_{c,r} \cdot PC_{c,r,t} \quad (6)$$

where subscript  $r$  is introduced to refer to market,  $C_{c,r,t}$  is the quantity of the irrigated crop product consumed in market  $r$  in year  $t$  during the simulation (ton/yr),  $PC_{c,r,t}$  is the consumer price of the product in market  $r$  in year  $t$  (\$/ton),  $\gamma_{c,r}$  is the intercept parameter of and  $\delta_{c,r}$  is the slope parameter of the linear demand function for product  $c$  and market  $r$ .

Demand functions describe relationship between prices and consumed quantities of products and could be shifted by exogenous factors such as population and income growth. The Ethiopia case study has a planning horizon of 2030. We did not simulate the shifts of demand functions dynamically in this study. Instead, the values of parameters of the demand functions were directly set to reflect the demand-price relationship in 2030. To this end, the intercept and slope parameters of the demand functions are first estimated using consumption and price data of around base year (circa 2010) and the intercept parameters were adjusted to account for the exogenous growth out to 2030. The sources of data used in the estimation process include Ethiopia CSA survey data

reports on production and retail prices (CSA, 2012 & 2015), FAOSTAT production and trade matrix databases, and price elasticities of demand, projected population and income growth rates retrieved from the literature (Tafere et al., 2010; Robinson et al., 2015). Of particular note, the national total production from Ethiopia CSA survey data reports, following adjustments based on export and import data reported in FAOSTAT trade matrix, was distributed to the eleven domestic markets based on population data to generate estimates of consumption of each product in the eleven domestic markets.

Prices in individual markets are linked to an equilibrium price via market margins which are constant parameters and introduced to reflect the structural price differences among markets,

$$PC_{c,r,t} = (1 + v_{c,r})PCE_{c,t} \quad (7)$$

and the producer price is translated into the consumer price by using consumer-producer price marketing margins:

$$PP_{c,r,t} = cpm_{c,r} \cdot PC_{c,r,t} \quad (8)$$

where  $PCE_{c,t}$  is the equilibrium price in year  $t$ ,  $v_{c,r}$  is the market margin between price in market  $r$  and the equilibrium price, and  $cpm_{c,r}$  is the margin indicating the price difference between the producer price and consumer price of irrigated product  $c$  in market  $r$ .

Let  $Q_{c,r,t}$  denotes total production of product  $c$  in market  $r$  in year  $t$  (ton/yr). By applying the market clearing condition, which states that total quantities supplied always equal total quantities consumed,

$$\sum_r Q_{c,r,t} = \sum_r C_{c,r,t} \quad (9)$$

$PCE_{c,t}$  is calculated as

$$PCE_{c,t} = \frac{\sum_r Q_{c,r,t} - \sum_r \gamma_{c,r}}{\sum_r \delta_{c,r} \cdot (1 + v_{c,r})} \quad (10)$$

For each market/region,  $Q_{c,r,t}$  is calculated as

$$Q_{c,t,r} = Q_{c,r,base} + \sum_{f \in r} (\gamma_{c,f} \cdot A_{c,f,t}) \quad (11)$$

where  $Q_{c,r,base}$  is the production of crop product  $c$  in base year and in region  $r$  (ton/yr), subscript  $f$  refers to farm,  $\gamma_{c,f}$  is the yield of product  $c$  in farm  $f$  under the expanded dry-season irrigated production (ton/ha) estimated through the SWAT simulation, and  $A_{c,f,t}$  is the farm size or area of the irrigated crop in farm  $f$  in year  $t$  (ha).

Producer-consumer price margins  $cpm_{c,r}$  are estimated using data on producer prices and retail prices from the CSA survey reports (CSA, 2012 & 2013). Values of market margins  $v_{c,r}$  are initialized in the simulation under base year consumer price-consumption conditions by rearranging Eqs. (7)-(10) and taking prices on regional markets as known. In Eq. (11) proposed to calculate annual total production  $Q_{c,t,r}$ , the second term is non-zero for domestic market and is the incremental production from the expanded dry-season irrigated production calculated by summing productions of all adopting farms in the region. In the long run, other farms will adjust production to respond to price change. The use of  $Q_{c,r,base}$  implies that we omitted this variation and production variability brought about by other factors in this assessment with short-term planning horizon. Finally, note that in Eq. (10),  $\sum_r Q_{c,r,t} < \sum_r \gamma_{c,r}$  and  $\sum_r \delta_{c,r} < 0$ ; an increase in production will lead to a drop in price.

At the end of growing season in each year, water budget of each basin is also re-assessed according to the "actual" number of adopting farms. If the estimated total irrigation water use exceeds amount of water available for irrigation in the basin, a subset of adopting farms where a failure of water supply is assumed to occur are randomly selected until water availability constraint is met. Yields of irrigated crops in those farms are set to zero in post-season profit evaluation.



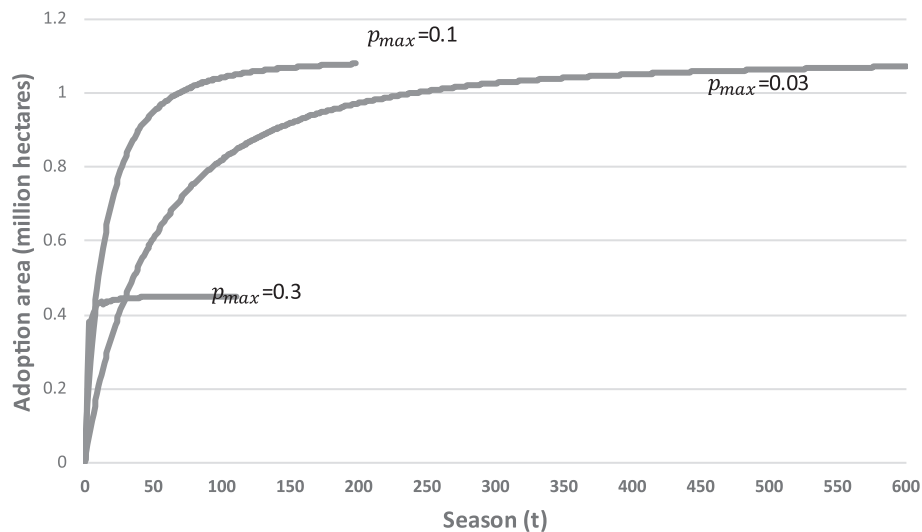


Fig. 6. Simulated adoption rates of small-scale dry-season irrigation in Ethiopia under alternative values of  $p_{max}$ .

### 2.3.5. Outputs

The pre-adoption and post-season evaluation processes are repeated until all potential adoption has taken place subject to water resources and market constraints. Since there is a stochastic element in the model (Eq. (5)), multiple model realizations are generated randomly. As the main output from the simulation, the model reports the adoption probability of dry-season, small-scale irrigation on a 1 km grid. The adoption probability of each farm pixel is calculated as:

$$p_{adopt} = \frac{n_{adopt}}{N_{sim}} \quad (12)$$

where  $p_{adopt}$  is the adoption probability of small-scale irrigation in the pixel,  $n_{adopt}$  is the number of realizations in which small-scale irrigation is adopted successfully in the pixel at the end of the simulation period, and  $N_{sim}$  is the number of total realizations.

The model also reports the probability of water scarcity at the 10 km basin level. The probability of water scarcity is calculated as:

$$p_{ws} = \frac{n_{ws}}{N_{sim}} \quad (13)$$

where  $p_{ws}$  is the occurrence probability of water scarcity in the basin,  $n_{ws}$  is the number of realizations where water resources available for irrigation are fully exhausted at the end of simulation.

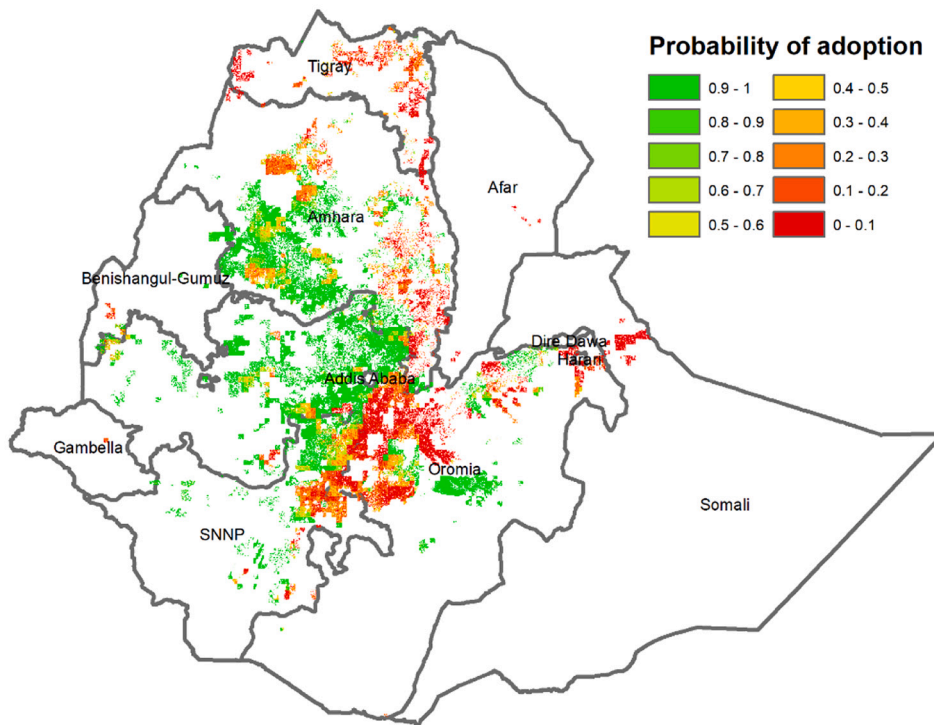
### 2.4. Model limitations, uncertainty and sensitivity analyses

Like all other modeling exercises, the agent-based irrigation planning model noted above is subject to limitations and uncertainty. For instance, the farms in the model are defined on an abstract landscape or by rainfed area on 1 km grid due to lack of detailed data on farm size distribution in real world. Another source of model structural uncertainty, which could be more prominent, is algorithm that is proposed to shape behaviors of agents in simulation. The adoption probability of irrigation at each individual farm is calculated using Eq. (5). A linear relationship between the environmental suitability score and the adoption probability in the formulation of this equation is assumed as there is no further knowledge to determine the functional form of the equation. There is also more fundamental uncertainty associated with this equation that relates to the fact that the adoption probability calculated in that way mainly reflects the influence of the biophysical environment on irrigation adoption. Evidence from empirical studies suggests that farmers' decisions on adopting agricultural technologies are correlated with their socioeconomic attributes, such as age,

education and current wealth (Namara et al., 2007; Adeoti, 2008; Gebregziabher et al., 2014). Past studies on technology diffusion also emphasize the role of social learning in the diffusion of technology (Czepiel, 1974; Young, 2009; Genius et al., 2013). The reason behind the under-representation of social variables in our model is two-fold: firstly, despite remarkable progress in behavioral economics and experimental economics, nationally representative knowledge of smallholder farmers' behavior in technology adoption in Sub-Saharan African countries is still limited; secondly, and just as importantly, "background" spatial data that map the distributions of relevant social variables are generally not available. Thanks to advances in remote sensing and downscaling techniques, rapid development of high-resolution data now better describe the biophysical environment, which greatly improves environmental suitability analyses for irrigation planning (Romanelli et al., 2012; Thapa et al., 2017; Wagesho and Nigussie, 2017). However, developing spatial data of social science variables with sufficiently high resolution is still challenging. It is also worth mentioning that farmers may cooperate with each other to form groups or organizations to manage irrigation collectively. For the same reasons noted above, farmers' collective behaviors are not modeled in this study. In fact, the model, in its current form, is designed to capture the interactions between agents (farms) due to the competition for water resources and market share of irrigated crops. The latter interactions created by national market becomes particularly important in an irrigation planning analysis at national scale.

When it comes to parametric uncertainty,  $p_{max}$  in Eq. (5) is a key parameter that determines the magnitude of the calculated adoption probability. In this study, the irrigation potential is defined by the saturation level of irrigation and therefore we run the model for a large number of iterations until saturation is reached. A small value, 0.03, was used to avoid the risk of "over-adoption", which may result in a premature saturation of irrigation expansion. Fig. 6 shows the adoption curves obtained from simulations with this and two alternative values for this parameter. Over-adoption occurs when a large value for  $p_{max}$  is specified (0.3 in the case shown in the Figure). This causes too many farms to enter irrigated agriculture simultaneously and the increased production of irrigated crops exceed the demand of the market. Consequently, the price crashes limiting the profitability of irrigated production. On the other hand, the estimate for irrigation development potential proved robust when over-adoption risk is eliminated. When  $p_{max}$  is set to 0.1, the model reports almost identical estimates for final adoption potential as with a  $p_{max} = 0.03$ , although the time required to reach the saturation level differs. Note that while a high value of adoption probability parameter leads to "over-adoption", a slow

(a) Adoption probability



(b) Probability of water scarcity

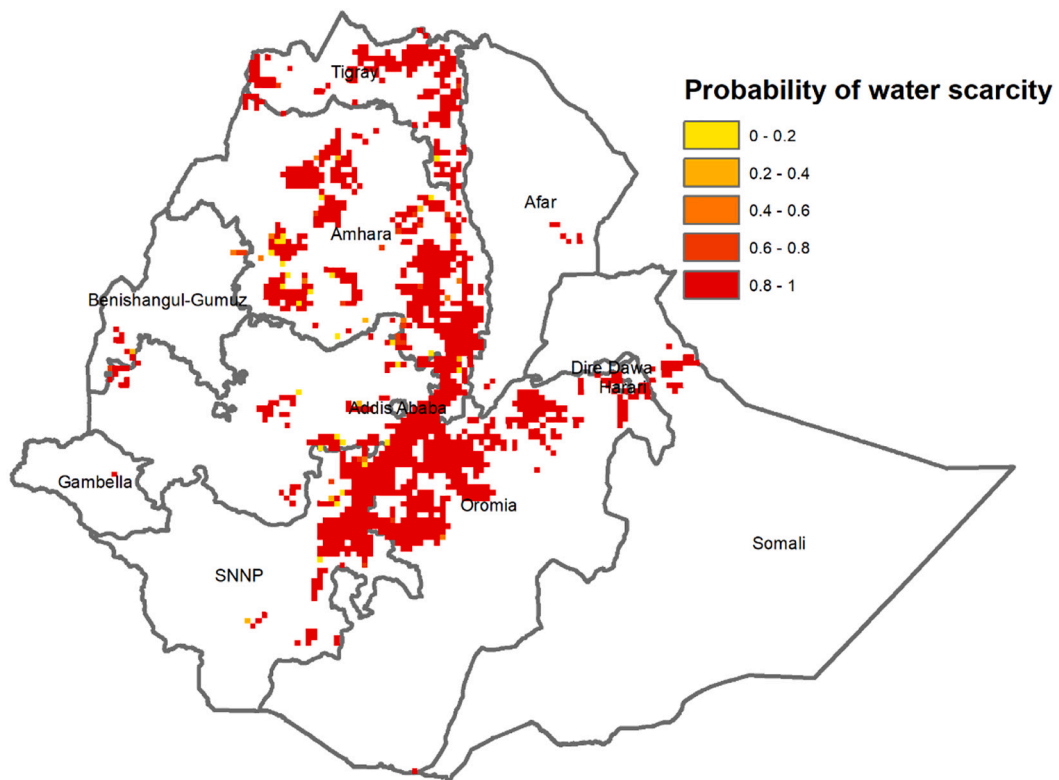


Fig. 7. Estimated development potential of dry-season small-scale irrigation and associated risk of water scarcity (baseline scenario)

**Table 2**  
 Estimated development potential of dry-season, small-scale irrigation in Ethiopia, baseline scenario.<sup>a</sup>

Region	Potential area (10 <sup>3</sup> ha)				Profit (10 <sup>6</sup> USD/yr)	Direct beneficiary population (10 <sup>3</sup> people) <sup>b</sup>
	Vegetables	Pulses	Fodder	Total		
Affar	0.04	0	0.03	0.07	0.15	0.14
Amhara	48	284	139	471	1092	857
Benishangul-Gumuz	3	11	2	16	42	30
Dire Dawa	0	0	0.1	0.1	0.13	0.13
Gambella	1	0	0	1	2.8	1.2
Harari	0	0	0.1	0.1	0.25	0.14
SNNP	39	43	41	123	421	741
Tigray	0.4	3	11	15	47	65
Oromiya	58	218	172	447	1095	1242
Somali	0	0	1	1	2	1.3
Total	149	560	365	1074	2703	2938

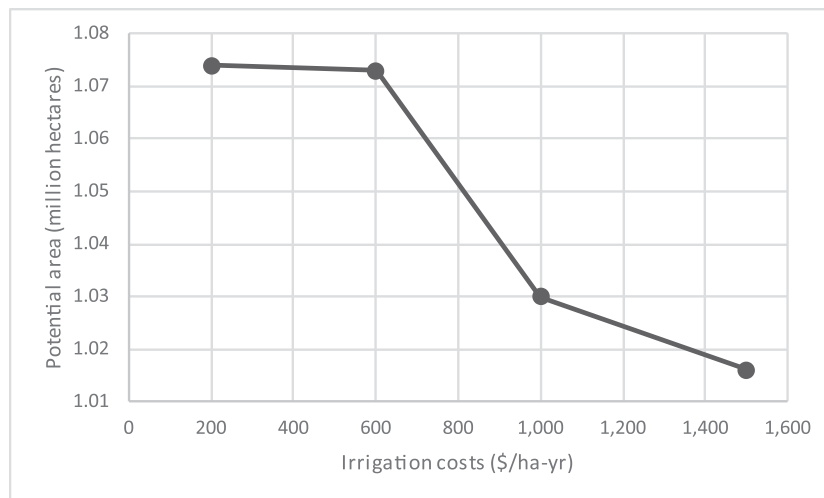
<sup>a</sup> Figures shown in the table are subject to rounding error.

<sup>b</sup> Direct beneficiary population =  $\frac{\text{Potential area (ha)} \times \text{People per household}}{\text{Farm size (ha)}}$ . Data on people per household and farm size by region are obtained from Ethiopia Rural Socioeconomic Survey report (CSA (Central Statistical Agency of Ethiopia) and World Bank, 2013).

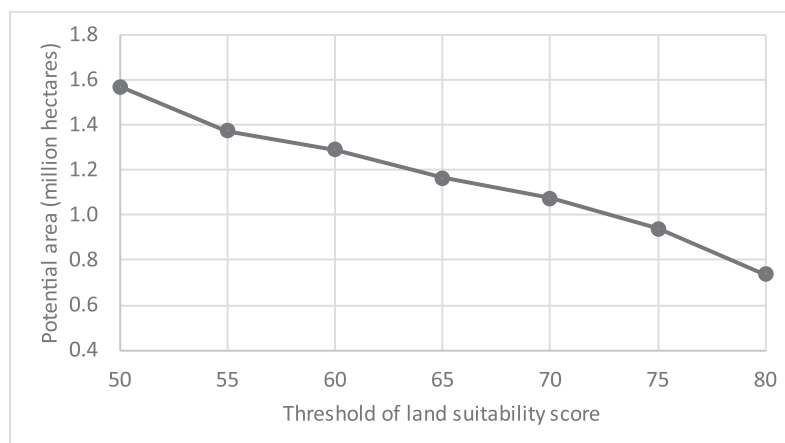
adoption rate may be linked with risk of “under-adoption”. In the model, static demand curves representing market opportunities for irrigated crops were used in the simulation (Section 2.3.4); in the real world the demand is dynamic, shifting upward with time due to population and

economic growth: when the adoption rate is low, actual adoption levels could always lag behind the growth of demand. The presence of risks of “over-adoption” and “under-adoption” implies outside interventions are desirable to ensure that the adoption potential can be fully tapped into

(a) With respect to irrigation cost (suitability score threshold =70 & water availability factor  $\alpha=0.06$ )



(b) With respect to environmental suitability threshold (irrigation cost = \$200 & water availability factor  $\alpha=0.06$ )



**Fig. 8.** Sensitivity of estimated irrigation development potential in Ethiopia

or a smooth expansion of small-scale irrigation. A series of institutional factors that influence irrigation technology adoption such as access to credit and extension services have been identified in past studies (Shah et al., 2002; Namara et al., 2011; Liverpool-Tasie and Winter-Nelson, 2012; Lefore et al., 2019). The omission of social variables in the current model restricts our ability to explore the implications of adoption rate in a simulation environment with dynamic demand and to simulate irrigation adoption under varying institutional settings. Addressing these limitations and uncertainty will be an important future research topic.

In addition to sensitivity analysis on  $p_{max}$ , sensitivity analyses were also conducted to quantify parametric uncertainty associated with the threshold of the pre-suitability score for irrigation adoption,  $S_{threshold}$ , in Eq. (5), the irrigation cost parameter in Eq. (1) and water availability factor  $\alpha$  in Eq. (4).  $S_{threshold}$  determines the spatial extent over which irrigation adoption could occur. Choice of its value involves subjectivity. While we used a base value of 70 in the simulation, we varied the value in sensitivity analyses between 50 and 80. The irrigation cost in Eq. (1) is an important parameter determining the economic profitability of irrigation. In the sensitivity analysis of irrigation cost, the irrigation cost value is increased to up to \$1500/ha-yr to reflect the additional costs that may incur for constructing water infrastructure that provides storage capacities required for the small-scale irrigation. Uncertainty of the water availability factor  $\alpha$  is discussed in Section 2.3.3. A high-water-availability scenario is applied in the sensitivity analysis in which the irrigation is assumed to be predominantly fed by groundwater. Aquifers can serve as underground reservoirs providing water storage to support the development of irrigation. Exploitable water resources in the high-water-availability scenario is set to 50% of groundwater recharge (Altchenko and Villholth, 2015) or about 20% of basin water yield on average (i.e., the water availability is almost tripled).

Results of the sensitivity analyses of these two parameters are presented in the results section together with the results generated with their base values.

### 3. Results

The results of the agent-based modeling for the Ethiopia case study using baseline values of irrigation cost and the environmental suitability threshold ( $N_{sim}=100$ ) are shown in Fig. 7.

The map in panel (a) shows the estimated adoption probability of small-scale dry season irrigation on a 1 km farm grid. The expected adoption areas over the whole country and by state are further summarized in Table 2, and are calculated by summing over pixel-wise adoption area multiplied by adoption probability. The national total of potential adoption area by 2030 was estimated at around one million hectares. Most of this identified adoption potential is located within the Amhara region, the Oromia region and SNNPR (Southern Nations, Nationalities, and Peoples' Region). All three areas form part of the high-potential Ethiopian Highlands agricultural area. The estimated potential area in the three regions are 0.47 million hectares, 0.45 million hectares and 0.12 million hectares, respectively and reflects a high-adoption-probability zone stretching from the central Amhara region to northern SNNPR. The last two columns of Table 2 also show the estimated profits farmers may have from adopting the small-scale irrigation and direct beneficiary population, which consists of households operating adopting farms. It is estimated that, nationally, those farmers adopting small-scale irrigation can earn a profit of \$2.7 billion per year and the size of direct beneficiary population is about 3 million people.

The map in panel (b) shows the calculated basin-wide probability of water scarcity. A large number of basins is found to be exposed to elevated risk of water scarcity arising from dry-season irrigation expansion. This result suggests that expansion of small-scale, dry-season irrigation in Ethiopia is strongly constrained by water scarcity. Note that the water availability constraints imposed in the model are "soft" constraints, which can be violated in actual irrigation development if there

**Table 3**

Estimated development potential of dry-season, small-scale irrigation in Ethiopia, high water availability scenario (environmental suitability score threshold =70, irrigation cost = \$200/ha-yr).

Region	Potential area (10 <sup>3</sup> ha)	Region	Potential area (10 <sup>3</sup> ha)
Affar	0.08	Harari	0.1
Amhara	645	SNNP	169
Benishangul-Gumuz	19	Tigray	42
Dire Dawa	0.1	Oromiya	568
Gambella	1	Somali	1
Total	1445		

is no enforcement of environmental regulations. Thus, appropriate institutional arrangements are urgently needed to complement the government's strong support for small-scale irrigation development. Otherwise, tensions over water allocation might well increase and negative environmental impacts associated with small-scale irrigation development will increase.

The sensitivity analysis of the estimated irrigation development potential with respect to irrigation costs and the threshold of the environmental suitability score is presented in Fig. 8. Changes in the parameter for irrigation cost leads to a small variation in potential area between 1.07 million hectares and 1.02 million hectares. As expected, higher irrigation costs result in smaller estimates of irrigation development potential. The small change in total potential area can be explained by the high profitability in dry-season irrigated crop production. On the other hand, although the estimated potential area is not sensitive to the variation in irrigation cost, profitability of the irrigated production could be affected substantially by the increased irrigation cost. When the irrigation cost increases to \$1500/ha-yr, the national total of the profit decreases from \$2.7 billion per year to \$1.4 billion per year. Note that the use of constant irrigation cost parameter in the simulation may lead to an omission of investment cycle which could exist in irrigation development. In each investment cycle, farmers may be faced with higher costs in first several years due to capital investment costs and a payback period of multiple years. The length of the investment cycle and cost profile in an investment cycle depends on the type of irrigation technologies and financial arrangements and therefore are highly uncertain. But if relevant information is available, the investment cycle can be incorporated in the simulation by delaying the evaluation on farmer's exit decision to the last year of each investment cycle. Additional sensitivity analysis also showed that the modeling results in this case study are not sensitive to the cost profile variation if the annual averages of irrigation costs in the investment cycle are the same.

The model exhibits greater sensitivity to the environmental suitability score threshold parameter: The estimated potential increases to 1.6 million hectares when an environmental suitability score threshold of 50 is used and declines to 0.7 million hectares when the threshold value is set to 80. These two alternative estimates may be considered as a more optimistic and conservative estimate of irrigation development potential in Ethiopia, respectively. In future applications of the model more formal procedures similar to Garthwaite et al. (2005) may be introduced to reduce subjectivity in specifying the value of this parameter.

Model results under high-water-availability scenario are shown in Table 3 and Fig. 9. Improved water availability from groundwater storage allows small-scale irrigation development potential to increase from 1 million hectares to 1.4 million hectares. Less water scarce area is found under this scenario, but the water scarcity risk originating from the small-scale irrigation expansion is still quite significant.

### 4. Conclusions

Small-scale irrigation offers an avenue for farmers in Sub-Saharan

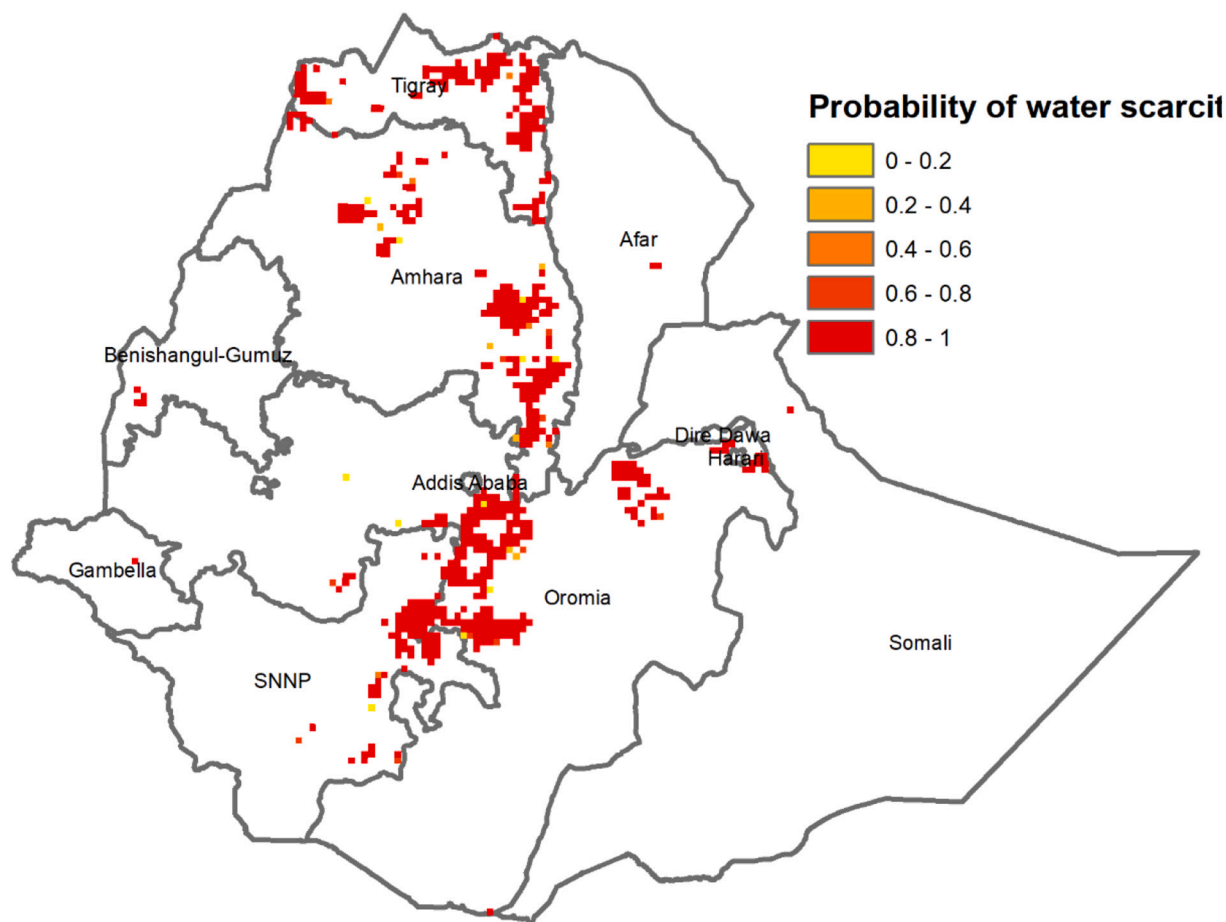


Fig. 9. Estimated probability water scarcity under high water availability scenario (environmental suitability score threshold =70, irrigation cost = \$ 200/ha-yr)

Africa to expand agricultural production in the dry season. This paper presents a new model, which uses agent-based modeling techniques to integrate information from GIS-based environmental suitability analysis, hydrological and economic modeling to generate estimates for dry-season, small-scale irrigation development potential in Sub-Saharan Africa countries.

The model is applied to Ethiopia to map sites with high adoption probability under the joint constraints of water availability and market opportunities. Model results vary across scenarios. Under the baseline scenario, it is estimated that in Ethiopia by 2030 there is potential to add about 1 million hectares of land irrigated by small-scale irrigation systems for crops of high value (0.15 million ha for vegetables and 0.56 million ha for pulses) as well as animal feed (0.37 million ha). The potential is concentrated in the Oromia region, the Amhara region and the SNNP region, which account for 42%, 44% and 11% of the estimated national potential respectively. The simulations also show a large portion of area with identified irrigation development potential could be subject to elevated risk of water scarcity due to the expansion of the small-scale irrigation. In these regions, appropriate institutional arrangements should be made in conjunction with small-scale irrigation activities investment, to reduce the negative environmental impacts of small-scale irrigation development.

#### Declaration of Competing Interest

There is no conflict of interest associated with this manuscript.

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#### Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.agry.2020.102987>.

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